# Brain Computer Interface: the use of Low Resolution Surface Laplacian and Linear Classifiers for the Recognition of Imagined Hand Movements

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*Abstract*- **EEG-based Brain Computer Interfaces (BCIs) require on-line detection of mental states from spontaneous or surface Laplacian transformed EEG signals. However, accurate SL estimates require the use of many EEG electrodes, when local estimation methods are used. Since BCI devices have to use a limited number of electrodes for practical reasons, we investigated the performances of spline methods for SL estimates using a limited number of electrodes (low resolution SL). In this paper, recognition of mental activity was attempted on both raw and SL-transformed EEG data from five healthy people performing two mental tasks, namely imagined right and left hand movements. Linear classifiers were used including Signal Space Projection (SSP) and Fisher's linear discriminant. Results showed an acceptable average correlation between the waveforms obtained with the low resolution SL and those obtained with the SL computed from 26 electrodes (full resolution SL). Recognition scores for mental EEG-patterns were obtained with the low-resolution surface Laplacian transformation of the recorded potentials when compared with those obtained by using full resolution SL (82%).**

## I. Introduction

In the framework of the construction of a EEG-based Brain Computer Interface (BCI) it was suggested that EEG patterns can be better detected with EEG data transformed with the Surface Laplacian computation (SL) than with the unprocessed raw potentials [1]. However, accurate SL estimates require the use of many EEG electrodes, when local estimation methods are used [2,3]. These local estimation methods compute the SL at a certain electrode position on the base of the value of the surrounding nearest electrodes. This cause errors in the SL estimation at the electrodes placed at the boundary of the electrode grid, since their neighbors are not well defined [4,5]. The requirement of an high number of electrodes for an affordable estimate of the SL of the EEG distribution would prevent the application of SL estimates in a BCI device to be used by laypersons in real-life conditions, due to practical reasons, namely the time consuming procedure of the scalp electrode positioning. On the other hand, there exists a class of estimators of the surface Laplacian of the EEG potential distributions that is based on the use of a "global" computational scheme, such as the spherical splines [6,7], in which the surface Laplacian at a certain electrode position depends from the values at all the other positions of the recording array. From these considerations, in this paper we investigate the performances of global computational methods for the estimation of the SL from a limited number of electrodes, based on the spherical spline approach. The working hypothesis at the base of the present work are i) the use of global interpolation SL estimates can produce reasonable SL waveforms even if a reduced number of electrodes are used (low resolution SL); ii) the use of low resolution SL waveforms for BCIs allows percentage of classifications of mental patterns statistically similar to those obtained with SL waveforms computed with the full recording array. In order to investigate the first issue, the "gold standard" of the SL estimates obtained with the full recording array were compared to the spline-based SL estimations obtained on the same EEG recordings but using only 9 electrodes, uniformly disposed along the scalp in the position of the international 10-20 system. The second issue was addressed by comparing the recognition rates of the BCI system obtained using low-resolution SL waveforms with those obtained by the full resolution SL. Here, we report results in the recognition of mental patterns with two linear classifiers based on the *Signal Space Projection* (SSP) algorithm [8] and Fisher's linear discriminant functions [9,10]. The interest in the use of such linear classifiers for BCI is due to their simple training and decision procedures. In fact, these procedures do not involve non-linear minimization procedures such as those necessary for the neural network classifiers already used in the BCI field [11-13]. This of course was at the expense of the possibility to separate the input space with non linear discriminant functions. Recognition performances of the two linear classifiers on unprocessed and SL-transformed EEG data were computed from a group of five healthy people performing two motor-related mental tasks, namely imagined right and left hand movements.

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## II. Methodology

### *A. Data Collection*

Five healthy subjects (three males and two females) participated voluntarily in experiments where they performed different tasks, including the imagination of the movement of the right middle finger (RI) as well as the left middle finger (LI). The whole scalp was covered with 26 EEG electrodes placed onto standard locations according to the extension of the 10-20 international system. Sampling frequency was 400 Hz, and signal was bandpass filtered between 0.1 and 100 Hz before digitization. At the beginning of a recording session, subjects remained in a resting state—relax with eyes opened—for 60 s. The EEG activity of this period is used as a baseline for subsequent analysis of the mental tasks. Then,

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**Abstract**

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subjects started performing the task immediately after the operator instructed them to do so, and they maintained that task for more than 10 s. Every subject executed four times each task during the recording session, with a resting period of 10 s between each. After removal of time segments contaminated with EMG in the arms it remains about 40 seconds of EEG signals for each task for every subject.

### *B. SL estimations.*

Surface Laplacian computations were performed by using the spherical splines of order two, that were found to be adequate to describe the SL distributions of EEG data [14]. For each EEG recording two computations of the SL were performed. The first by using all the information of the electrode montage (full-resolution SL), while the second SL computation was performed by using only the data of the EEG potentials from nine electrodes (low-resolution SL). These nine electrodes were placed on the scalp surface according to the position F3, Fz, F4, C3, Cz, C4, P3, Pz, P4 of the International 10-20 System.

### C. *Comparisons of the SL estimations*

The aim of the work was to investigate if the low-resolution SL estimation is able to produce relatively accurate SL estimates for the recognition of mental patterns. Hence, we used the correlation coefficient to measure the fit between the full resolution and the low-resolution SL waveforms in the nine electrodes selected. These comparisons were performed for all the EEG recordings performed in the five subjects analyzed.

### *D. Data Pre-Processing.*

Time varying spectrograms of either full and low resolution SL-transformed EEG data by estimating the Power Spectral Density (PSD) of 2-second long epochs, each starting 1 s after the previous one were computed. The Welch periodogram algorithm to estimate the PSD was applied. Epochs are divided into segments of 1 s, with a Hann window of the same length applied to each segment, and 50 % overlapping between the segments. This gives a frequency resolution of 1 Hz. Finally, the power components are referred to the corresponding values of the estimated PSD of the baseline and transformed in dB—i.e., we take the logarithm of the division. The spectral values were considered in a frequency band from 8 to 30 Hz, since those band was recognized to be useful for the recognition of mental pattern in previous papers [15,16].

### *E. Signal Space Projection*

In the Signal Space Projection method a *n*-dimensional space is defined so that a “measure” vector $\mathbf{m}(t)$, whose components are features extracted from incoming data, is represented in that space by a point. In the present case, the measure vector $\mathbf{m}(t)$ is the SL-transformed spectral EEG data in the frequency band of 8-30 Hz computing during the mental tasks analyzed. Given *p* vectors of *n*-dimensional “patterns” ($\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_p$), the *p* components of the “activation” vector:

$$\hat{\mathbf{a}}(t) = \mathbf{S}^{+} \cdot \mathbf{m}(t) \tag{1}$$

weight the presence of each pattern in $\mathbf{m}(t)$. $\mathbf{S}^{+}$ is the pseudoinverse of the projection matrix $\mathbf{S}$ whose columns are the patterns ($\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_p$). The pattern describing one of the i^th experimental tasks $\mathbf{s}_i$ is the mean of the selected components of the PSD computed while subject was imagining or performing the corresponding single hand movement (right or left) (training procedure).

### *F. Fisher’s linear discriminant*

The same input pattern array $\mathbf{m}(t)$ described before can be classified with a general linear discriminant function such as

$$y(t) = \mathbf{w}'\mathbf{m}(t) \tag{2}$$

where $\mathbf{w}$ is the array of unknown weights that defines the separation between classes of right imagined movement (RI) and left imagined movement (LI) in the input space. It is possible to define a projection that maximizes the separation between the classes. Fisher’s discriminant [9,10] maximizes a function $J(\mathbf{w})$ that represents the differences between the projected class means, normalized by a measure of the within-class scatter along the w direction. By defining $\mathbf{s}_R$ and $\mathbf{s}_L$ as the class means composed by the same spatial patterns used for the application of the SSP described before, and the average of the data set s, the function proposed $J(\mathbf{w})$ is

$$J(\mathbf{w}) = \frac{\mathbf{w}'\mathbf{R_b}\mathbf{w}}{\mathbf{w}'\mathbf{R_w}\mathbf{w}} \tag{3}$$

where $\mathbf{R_b}$ is the between class covariance matrix given by

$$\mathbf{R}_{\mathrm{b}} = (\mathbf{s}_{\mathrm{L}} - \mathbf{s}_{R}) \cdot (\mathbf{s}_{\mathrm{L}} - \mathbf{s}_{R})' \tag{4}$$

and $R_w$ the within-class covariance matrix given by

$$\mathbf{R}_{\mathrm{w}} = \sum_{t \in \mathrm{T}_1} (\mathbf{m}(t) - \mathbf{s}_R) \cdot (\mathbf{m}(t) - \mathbf{s}_R)' + \sum_{t \in \mathrm{T}_2} (\mathbf{m}(t) - \mathbf{s}_{\mathrm{L}}) \cdot (\mathbf{m}(t) - \mathbf{s}_{\mathrm{L}})' \tag{5}$$

where the first summation runs over all the patterns belonging to the class describing the right mental imagery and the second over all the patterns belonging to the class related to the left mental imagery. $J(\mathbf{w})$ is maximized when the weights are chosen proportionally to the $\mathbf{R}_{\mathrm{w}}^{-1} \cdot (\mathbf{s}_L - \mathbf{s}_R)$. Once obtained the weight vector w, the generic input pattern $\mathbf{m}(t)$ were assigned to the class regarding the left mental imagery if the result of the projection $\mathbf{w}' \cdot (\mathbf{m}(t) - \mathbf{s})$ is greater than zero, and to the class related to the right mental imagery otherwise.

### G. *Classification of mental patterns*

After PSD values were computed on full and low resolution SL-transformed EEG data, such values are then fed to into the linear classifiers used in this paper, based on the Signal Space Projection (SSP) and Fisher discriminant technique. These classifiers were then used for the separation of mental patterns related to the imagination of right (RI) and left (LI) hand movements.

### H. *Cross validation.*

For recognition purposes, we applied to the low and full resolution SL EEG data the k-fold cross-validation, with k = 8. Hence, we divided the EEG data set for each subject into k subsets of equal size. The SSP and Fisher linear discriminant projection were recomputed k times, each time leaving out one of the EEG data subsets from the training, and using the omitted subset to compute the recognition rate. Then, the results presented here are an average of the recognition rate obtained for each one of the k subset of EEG data not used for the SSP and Fisher estimation of the class means (training).

### I. *Statistical analysis.*

A two way Analysis of Variance (ANOVA) was performed on the average values of the recognition scores obtained by the cross-validation technique. The first main factor was METHODS with two levels (SSP and FISHER) for the linear classifiers used in the present work, while the second main factor was SPATIAL FILTER, with two levels (LOWRESL and HIGHRESL) in which the different implementation of the computation of the surface Laplacian are compared (low and high resolution SL). No spherical correction has been used [17] for the ANOVA computation since the levels of the main factors are less than three.

## III. Results

Table 1 reports the average correlation values obtained between the unprocessed EEG waveforms, the low-resolution and full-resolution SL transformation of the EEG waveforms, in each time point acquired and on all the five recorded subjects. Correlation values were computed for the channels included in the computation of the low-resolution SL, namely F3, Fz, F4, C3, Cz, C4, P3, Pz, P4. The first row of the Table 1 shows the correlation values between the low-resolution SL and the full-resolution SL on each channel analyzed. Average correlation between low and full resolution SL-transformed EEG waveforms was 0.65, while was 0.36 between the unprocessed EEG and the low-resolution SL waveforms, and was 0.38 between the unprocessed EEG and the full resolution SL waveforms. Table 2 reports the recognition scores (in percentages) of the mental imagination of movements in the five subjects analyzed with both the linear classifiers used (SSP and Fisher) with data from low and full-resolution SL. With SSP using the low resolution SL EEG data the average recognition was of 81.3% while using the full resolution SL improves to 82.1%. The use of Fisher classifier applied to the low resolution SL EEG data produces 60% or recognition score, while when the full resolution SL data was used this percentage arrives to 70.4%. The ANOVA demonstrated that the use of SSP improves significantly the recognition score with respect the use of Fisher discriminant method (METHODS main factor, F = 11.75, $p<0.0266$). Instead, the use of the low resolution SL data does not decrease significantly the recognition rate of the mental patterns with respect to the use of full resolution SL (SPATIAL FILTERS main factor, F = 3.79, p = 0.12). Furthermore, no interaction METHODS x SPATIAL FILTERS was found (F = 2.90, p = 0.16).

TABLE I

FIRST ROW: CORRELATION VALUES BETWEEN THE LOW-RESOLUTION SL AND THE FULL-RESOLUTION SL (SL9-SL). SECOND ROW: CORRELATION VALUES BETWEEN THE LOW-RESOLUTION SL AND THE RAW POTENTIALS (SL9-P). THIRD ROW: CORRELATION VALUES BETWEEN THE SL ESTIMATION OBTAINED USING ALL 26 AVAILABLE CHANNELS AND RAW POTENTIALS (SL-P)

| | **F3** | **C3** | **P3** | **Fz** | **Cz** | **Pz** | **F4** | **C4** | **P4** |
|---|---|---|---|---|---|---|---|---|---|
| **SL9-SL** | 0.41 | 0.82 | 0.59 | 0.5 | 0.9 | 0.91 | 0.37 | 0.78 | 0.57 |
| **SL9-P** | 0.39 | 0.26 | 0.27 | 0.5 | 0.5 | 0.43 | 0.46 | 0.11 | 0.34 |
| **SL-P** | 0.33 | 0.46 | 0.58 | 0.1 | 0.3 | 0.42 | 0.31 | 0.32 | 0.60 |

TABLE II

RECOGNITION SCORES FOR THE DETECTION OF RIGHT AND LEFT IMAGINED MOVEMENTS IN FIVE SUBJECTS. PERCENTAGES ARE OBTAINED WITH THE USE OF THE SSP LINEAR CLASSIFIERS WITH THE LOW RESOLUTION SL-TRANSFORMED EEG DATA (SSP LOWRES SL) AND WITH THE FULL RESOLUTION SL-TRANSFORMED EEG DATA (SSP FULLRES SL), AS WELL AS WITH THE FISHER LINEAR CLASSIFIER ON LOW AND FULL RESOLUTION SL-TRANSFORMED EEG DATA (FISHER LOWRES SL AND FISHER FULLRES SL, RESPECTIVELY)

| **Subjects** | **SSP LowRes SL** | **SSP FullRes SL** | **Fisher LowRes SL** | **Fisher FullRes SL** |
|---|---|---|---|---|
| Cl | 69% | 88% | 49% | 57% |
| Mj | 97% | 88% | 57% | 70% |
| Ra | 64% | 60% | 51% | 57% |
| Rb | 87% | 82% | 78% | 83% |
| Ta | 89% | 92% | 65% | 85% |
| Mean | 81% | 82% | 60% | 70% |

## IV. Discussion

The results of this study suggested that in the BCI framework it is useful to compute the surface Laplacian by spherical spline also if a limited number of scalp electrodes are available or used for the analysis. In fact, the accuracy of the computed low-resolution SL seems to be not too far from that of the SL obtained by 26 scalp electrodes (average correlation coefficient 0.65 on all the subjects and on all the time points analyzed). It is relevant that the SL-transformed waveforms with both modalities (low and full resolution) showed a very low correlation with the unprocessed raw potentials (about 0.38 for all SL-transformed potentials). More importantly, the average mental patterns recognition score over five subjects and for the SSP classifier obtained with the use of low-resolution SL are close to that computed with the SL computed from all the 26 electrodes used (81.3% and 82.1%, respectively). Statistical analysis performed with the ANOVA demonstrated that the use of low resolution SL data does not decrease significantly the performance of the particular classifiers used (i.e. SSP or Fisher, p = 0.16). This result is promising for the realization of BCI devices that rely on the use of a limited number of electrodes, also at the expenses of a minor recognition rates that maybe can be compensated by a relative larger training of the experimental subject. Such devices can compute the SL transformed EEG data by using global spline SL techniques with a modest loss of accuracy in recognition rates of mental patterns with respect to the case of in which a large array of electrodes is required. Statistical analysis also suggests the superiority of the Signal Space Projection as a method for the detection of mental patterns with respect the other linear discriminant technique, namely the Fisher linear discriminant. Compared to neural networks [10,12], linear classifiers are easier to train since they do not require non-linear minimization. With respect the recognition scores obtained here, other Authors have been able to perform successful recognition scores of patterns associated with the preparation of performed movements with linear classification technique based on the Common Spatial Patterns as high as 90% (CSP) [15] as well as non linear classifiers as high as 84% [11-13] in the BCI area.

In summary, results of the present work suggest that a BCI device based on linear classifiers and Laplacian-transformed EEG signals computed from a limited number of scalp electrodes (nine) can be able to detect mental activity with a reasonable level of percentage score. This open the avenue for more practical BCI devices that does not requires the use of a large set of electrodes.

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